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Driver Behaviour Modeling With Vehicle Driving Simulator

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Abstract: This paper describes the creation of a vehicle driving simulator that collects and implements data acquired from a driver's inputs. These data are stored for future analysis of the driver and his style of driving. The paper explains vital steps of the process such as theoretical background for modelling human behaviour, analysis of typical traffic situations that offer relevant information about a driver, simulator scenarios that reflect such traffic situations and an overview of gathered data.

Keywords: Vehicle driving, human behaviour modeling, simulator, data acquisition

1. INTRODUCTION

The first part of this paper is focused on the analysis of current procedures for modeling human driver behaviour with focus on car driving. So far, most of the actual driver models are based on a compensatory model, which does not include some of the aspects of the driver, for example his experience and driving style. An innovative approach on this subject is presented with a greater focus on human learning and adaptation during multiple test drives, which is yet to be implemented in the future. The second part of this paper is about the vehicle driving simulator. There are hardware components vital to the simulator, such as the driver's seat, the steering wheel, pedals and a gear stick which are used to simulate the conditions of a real car driving. Unique driving scenarios are implemented for acquiring different information about the drive. For the creation of this simulator, the Unreal Engine developed by Epic Games is used, as it offers a user-friendly environment with multiple tools and assets necessary for this project. A simulator application was created from the ground up with the usage of free available assets. At the end of this article, a sample of measured data is presented.

2. HUMAN BEHAVIOUR MODELING

According to Havlíková et al. (2014), man-machine systems (MMS) are formed when a human (controller) is using a complex tool – a machine. In our case, a typical example of such a system is a person driving a car. If an effective and successful control of this system is desired, it is necessary to have a properly designed controller. We, as human beings, could be considered as such a controller, because we deal with control tasks every day. We are facing unexpected situations with changing conditions and we are forced to learn, to adapt. From this point of view, we can assume that a person is a very effective and universal controller. Regulatory interventions in man-machine systems change based on our experience. It can be safely said, that a person represents a form of a learning, adaptive controller and its attributes correspond with those of a common industrial controller. Behaviour of such 'human controllers' can be mathematically represented and evaluated. Needless to say, an important part of human behaviour cannot be unaccounted for – and that is human consciousness.

MMS are based on a mutual cooperation between a human and a machine. In such systems, a person executes a variety of operational and control actions. A knowledge of such actions, together with a machine model, is necessary for a faithful recreation of a whole system. If such a model is developed, it could be used to monitor the system as a whole and draw conclusions from simulations. Operator's actions are dependent on the complexity of such a system and can be divided into multiple categories. According to Rasmussen (1986), these actions are divided into three categories/levels, as seen in Fig. 1:

Skill-based behaviour
The lowest level of MMS control without conscious control. It is based on fast and automated motor programs, which control the appropriate muscles. A typical everyday example of a skill-based task is walking. From a driver's point of view, such tasks are: starting the vehicle, keeping the vehicle in lane or keeping the velocity of the vehicle according to speed limit (Havlíková (2008)). In this case, human musculoskeletal system is considered as a controller. Sensory input is a continuous signal, for example a visually perceived information of the driver's surroundings (Wentink et al. (2003)).

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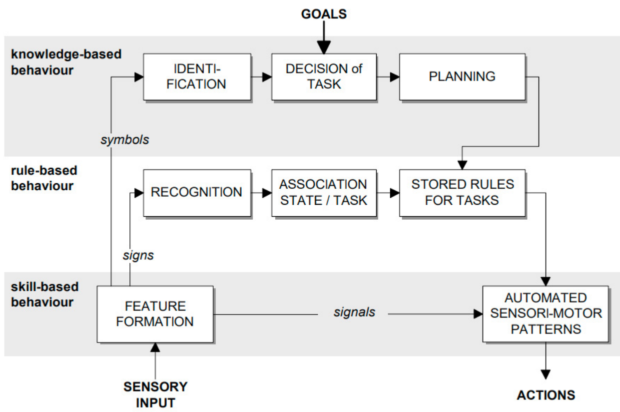

Fig. 1. Human behaviour model by Wentink et al. (2003)

Rule-based behaviour
At this level, more difficult tasks are recognized and associated with a specific execution based on rules or learned procedures. Such executions could be derived from a person's experience or learned from other person's instructions (Wentink et al. (2003)). An example of such a task is overtaking, turning or driving according to traffic signs (Havlíková (2008)).

Knowledge-based behaviour
The highest level of human control behaviour. Multiple symbols are perceived and analysed. According to overall goals, an optimal plan is being created based on a person's knowledge and experience (Wentink et al. (2003)). For example, a driver analyses the traffic or the behaviour of other drivers and reacts accordingly, e.g. slowing down or overtaking (Havlíková (2008)).

2.1 Innovative approach to human behaviour modeling

As Mulder et al. (2018) state, most of the current human behaviour models are based on technology and methods formed in the 1960s, which limit the understanding of human cognition and control. Modern cybernetics theory describes human controllers as LTI feedback systems. The time-invariance factor limits the most important aspect of human control – the ability to learn and to adapt to changing situations. Needless to say, simple human behaviour offers much easier experimental validation (Havlíková (2008)).

In the 1960s, a Succesive Organization of Perception (SOP) hierarchy for human control was established by Krendel and McRuer (Krendel and McRuer (1960)). The hierarchy is divided into three phases – compensatory, pursuit, and precognitive control. In the compensatory phase (shown in Fig. 2), a human controller acts only on the error information feedback between the output of the system and the desirable input. Most of the current-day methods rely on this single-loop compensatory phase, mainly because of its simplicity and easier tracking of human controller adaptation (Mulder et al. (2018)).

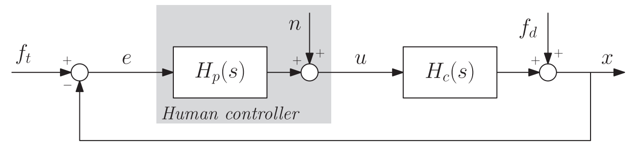

Fig. 2. Single loop compensatory model by Mulder et al. (2018)

The multi loop pursuit model offers a combination of a feedforward response (H_{Pt}), a compensatory feedback response (H_{Pe}) and a system output feedback response (H_{Px}), as shown in Fig. 3 (Krendel and McRuer (1960)). Pursuit models did not receive that much attention because of the complexity of its modeling (Mulder et al. (2018)).

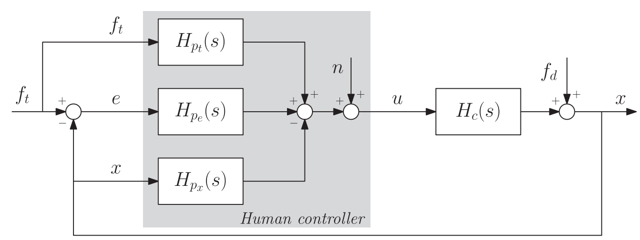

Fig. 3. Multi loop model by Mulder et al. (2018)

According to (Krendel and McRuer (1960)) the precognitive model (shown in Fig. 4) is dependent on the knowledge of a human controller. During this phase, human controllers may have developed a pure open-loop control responses based on a representation of the controlled system dynamics and other attributes. A controller does not rely on any feedback.

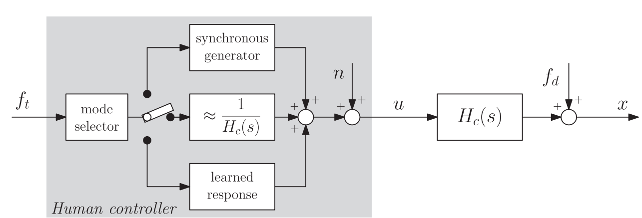

Fig. 4. Open loop pre-cognitive model by Mulder et al. (2018)

Most of today's methods make use of compensatory tracking, which is quite distant from real-world scenarios (Mulder et al. (2018)). For a more detailed approach on this subject, a five-step framework was proposed by Mulder et al. (2016). Each of the steps expand the current cybernetics view on human behaviour modeling, as shown in Fig. 5. The core of this proposed model is the *Internal Representation*, that is expanded and developed during learning while a human controller is exposed to certain tasks.

The first two steps, pursuit and preview, add a necessary feedforward component to ensure the applicability of such cybernetic models for real-life human control tasks. Usefulness of this component can be seen in current haptic

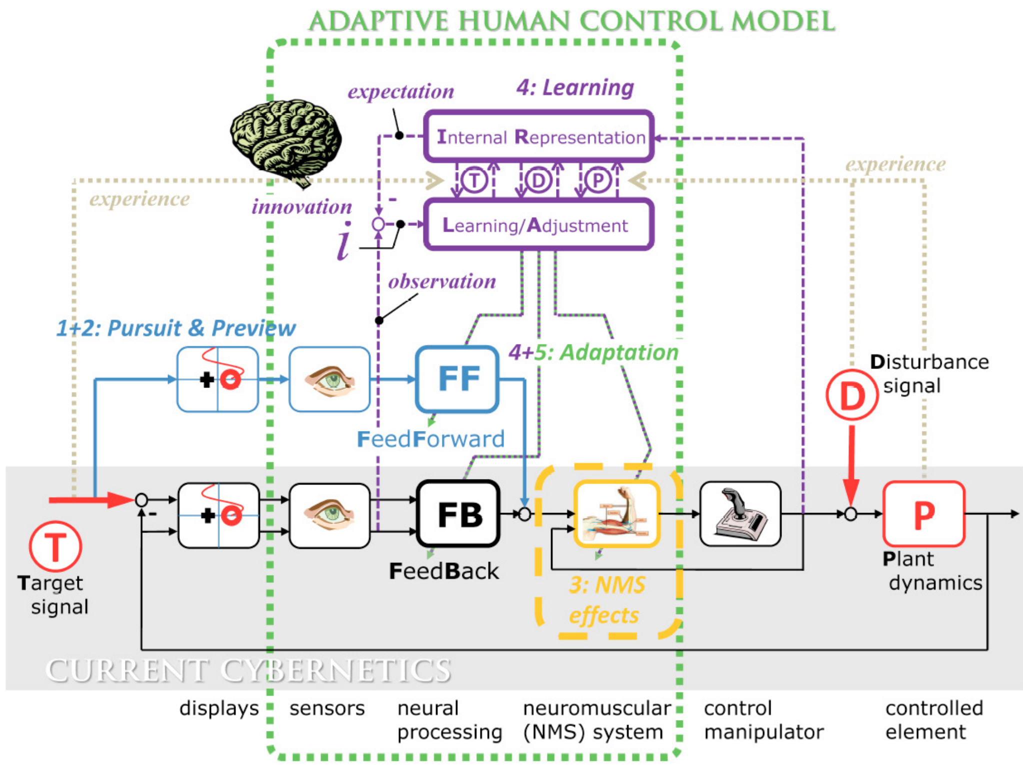

Fig. 5. Human control model by Mulder et al. (2016)

shared control systems, that rely on the visual preview of the road ahead (Mulder et al. (2018)). During learning, an internal representation is changed not only because of higher level cognitive adaptations, but also because of the adaptation of neuromuscular system (Mulder et al. (2016)). Example of such adaptation could be experience gained from multiple repeating scenarios – lane changing or turning (Havlíková (2008). In order to better understand human controller, synergy between 'low level' neuromuscular adaptations and higher level learning needs to be studied.

Steps four and five, learning and adaptation, work closely together. During learning, a human controller is being developed into an expert controller for a fixed set of task variables while maintaining balance between control effort and performance (Mulder et al. (2018)). Adaptation is when a human controller changes control strategy to another when task variables change (Mulder et al. (2016)) (in Fig. 5, P stands for plant dynamics, T stands for statistical properties of the target and D stands for disturbance signals) . While a human controller is learning, its internal representation is evolving. To better understand the process of learning, experiments and measurements need to be undertaken during the whole learning phase between a simple starting controller to a more complex expert controller.

When task variables begin to vary, human controllers may detect such changes because the expected state they obtained from their internal representation does not match the observed state. Machine system/model may respond differently, so an innovation is needed. This triggers a development changes in feedback control, feedforward control and neuromuscular system (Mulder et al. (2018)). This can be observed by the combined green-purple parts in figure 5. In order to better understand how human controllers behave, experiments and simulations with defined task variables with observation focused on learning and development of internal representation need to be undertaken.

2.2 Measured driver parameters in multiple scenarios

Human behaviour modeling theory was analyzed in order to create corresponding scenarios. Several driving situations were researched by Havlíková (2008) and they are as follows:

- Following a specific route – simulates a situation in which a driver must stabilize a vehicle in certain borders. Simple example of driving in a single lane. Slight inputs using a steering wheel are needed in order to do so.
- Driver's reaction time analysis – measuring sudden changes during a ride. Corresponds with unpredictable real-life situations in which a driver must react as swift as possible. An example of such a situation could be a dangerous object, that suddenly entered a vehicle's path.
- Driving style analysis – during longer rides where patterns in driver's behaviour could be monitored. For example the level of acceleration or steering wheel

handling.

3. REALIZATION OF THE SIMULATOR

In order to monitor a driver safely and to acquire relevant data, it is necessary to create a car driving simulator application. Several key elements need to be implemented:

- Core framework – according to (Lemarchand (2013)), creating an application without a game engine would be time consuming and would require knowledge, that is not necessarily needed in order to research human driver behaviour. Game engines offer such framework with useful tools and assets that could be used. A research about game engines had taken place. The selection was between open source game engines CryENGINE, Unity and Unreal Engine. In the end, Unreal Engine was chosen because of its user-friendly environment, helpful community and a lot of available assets, like the physical vehicle model implemented by NVIDIA's PhysX.
- Scenarios that simulate real-life situations. Key attributes of a driver could be extracted based on theoretical analysis of a human driver behaviour.
- Simulator contruction – necessary hardware components that simulate driver's cabin. A steering wheel with appropriate accuracy and degree of freedom, pedals, gear stick, a desktop monitor with a wide field of view and other components.
- Data measurement and analysis

3.1 Unreal Engine core framework

Unreal Engine offers a 3D visual environment in which a creation of a virtual world becomes possible. If we want a driver to feel immersed in the simulation, a quality replica of real-life environment needs to be created. With that in mind, a fictional environment with roads and real-life objects like mountains, hills, buildings etc. was created. Later on there is a need to create a larger map that would represent a whole city with functional traffic and driving rules.

A vehicle model with implemented armature was included as a *Wheeled Vehicle* object. This object is based on NVIDIAs PhysX vehicle model and controls the behaviour and collision of the vehicle inside the virtual world. This object incorporates vehicle model, armature, tyre configuration, animation, physics and connected input devices for vehicle control. Wheel and tyre configuration files determine the amount of wheel rotation or friction the vehicle has with the landscape. Other than that, the model is based as a single object with a calculated centre of mass. The Wheeled Vehicle object handles a user's input, which means that the steering wheel that is used is connected to the angle of the tyres (which is limited to be more realistic). Pedals are connected to the acceleration and decceleration of the vehicle. The object can handle an automatic or a manual gear change.

3.2 Input devices

The vehicle in Car Driving Simulator can be controlled via the Logitech G920 steering wheel and pedals. The steering wheel has a rotation range of 900 degrees from stop to stop and feedback with two motors. The brake pedal is non-linear - corresponding to a more real pedal. There is also a Driving Force Shifter gear stick. Everything is put together in a design with a seat and a widescreen monitor (as seen in Fig. 6).

Fig. 6. Vehicle driving simulator seat

3.3 Scenarios

Several scenarios have been created in the application to simulate situations in which it is suitable to acquire data about a driver.

Highway – step response
The scenario includes a highway map which is over 8 kilometers long and has no curves – it is a long and straight route. The user who chooses this scenario appears on the highway with his vehicle, and his task is to follow the line that appears when the scenario is turned on. The maximum speed of the vehicle is chosen by the user or the manager of the simulator (it can be changed either in the main menu or when the application is paused). When the maximum speed is reached, the position of the line which the user must follow will change. This change is conditioned by keeping the velocity around the desired speed and the randomly generated lag time delay between 10 and 30 seconds. There are 2 line positions possible and they are set to switch when the conditions are fulfilled. Once the vehicle passes the trigger volume (a part of the map), it is the end of the scenario.

Highway – long distance ride
Again, this scenario comprises a long motorway, although in this case it has long turns. Therefore it is not a straight route. The purpose of this scenario is to measure driver's behaviour during a long ride and his ability to maintain attention and keep the same direction. The main measured data is the distance from the line that the user must keep as small as possible. However, the position of the line does not switch as compared to the step response scenario.

Town scenario
The city map contains a lot of curves and shorter or longer routes. The main purpose of the scenario is to allow user to try the vehicle and to force him to frequently change speed, accelerate and brake. During the scenario, the route the user travels through is stored, so that it can be compared to his previous rides. With the other measurement results, we can create the ideal path the user should follow. In the future, this scenario can be used with algorithms for autonomous control and the measured routes can be compared to those which were driven by actual drivers. This could determine the algorithms reliability or the drivers efficiency.

Moose test scenario
This is a scenario based on a real measurement of the behaviour of vehicles on short routes. Its aim is to test the stability of the vehicle and the reliability of the vehicle model implemented in the simulator. As stated by Constant (2012), the progress and execution of the test is based on the automobile manufacturers' agreement to uniform vehicle testing so that the results of the tests can be easily compared and unified. The test is defined by ISO 388-2:2011 – it defines the dimensions of the test track, the maneuver performed, the required vehicle dynamics and the surface grip. This test can be applied to passenger cars defined by ISO 3833 and light commercial vehicles up to a maximum of 3.5 tonnes.

4. TESTING THE SIMULATOR AND DATA ANALYSIS

Car driving simulator was tested on a desktop PC with Windows 10. Overall look of the simulator seat with input devices is shown in Fig. 6, while a driver's view can be seen in Fig. 7. The driver was tested in multiple scenarios, which were mentioned above (Highway – step response, highway – long distance ride, town and Moose test scenario). Measured data was dependent on the scenario the driver was in, as shown in table 1.

Table 1. Data measured from the scenarios

Scenario	Data measured
Highway – step response	Distance from the line, steering wheel angle
Highway – long distance ride	Distance from the line, steering wheel angle
Town scenario	Steering wheel angle, velocity, X and Y coordinates
Moose test	Steering wheel angle, velocity

Distance from the line represents the difference in metres between the car's position and the line position (which can be seen in 7). Steering wheel angle is the amount of steering wheel rotation in degrees. This can be considered the most valuable data input from the user. X and Y coordinates represent the vehicle's position in the virtual world and velocity stands for car velocity in kilometres per hour.

The Highway – Step response scenario allows obtaining user response time information. Step changes in the lines position can be seen in the Fig. 8. The user was forced to react to this change by changing the position of the steering wheel (and thus the vehicle). The negative values of line distance in the Fig. 8 determine the distance from the right to the observed line, while the positive values determine the distance from the left. By comparing these two step scenario data sets – steering wheel angle and line distance – data about reaction time of a driver are extracted. The test drive was done with a single subject. Average value of the driver's reaction time was 610 ms with a standard deviation of 60 ms.

Fig. 7. Car Driving Simulator first person view

In the Highway – Long distance ride scenario, the position of the observed line does not change suddenly, but gradually. This way, curves on the highway are simulated. The task of the user is to keep the distance between the line and the vehicle as small as possible. Minor driver impulses are observed in Fig. 9 to maintain a stable distance. From this data it is possible to analyze the physical state of the driver and how fatigue or inattention affect his driving (Havlíková (2008)).

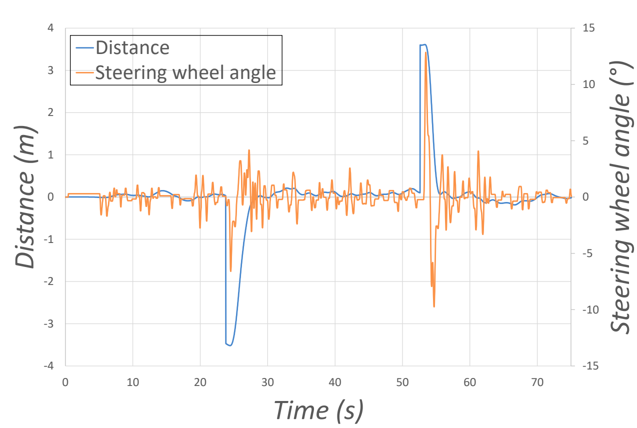

Fig. 8. Distance from line and steering wheel angle in Step response scenario

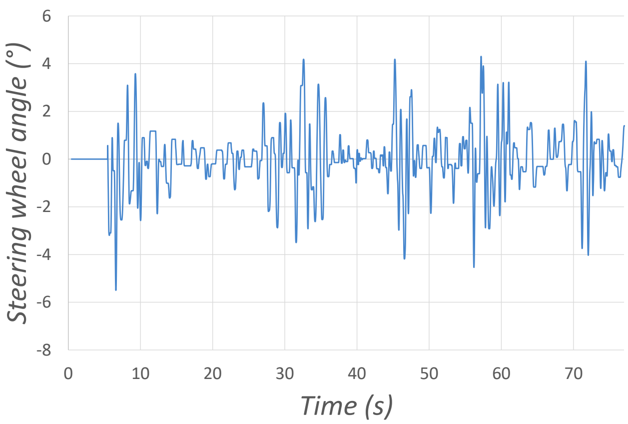

Fig. 9. Steering wheel angle in Highway – turns scenario

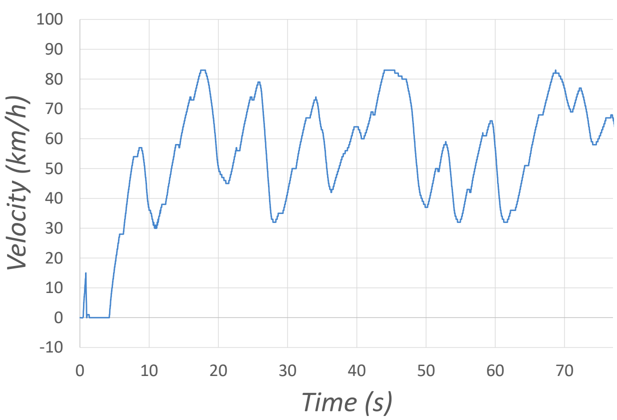

Fig. 10. Car velocity in Town scenario

The course of the velocity in Town scenario can be observed in the Fig. 10. It also corresponds to the characteristics of the track the user must go through. There is a constant change in speed, braking, steering wheel positioning etc. From these values, an appropriate analysis of the operator's (driver's) driving style can be obtained – for example, if there is an aggressive driver with sudden steering wheel turning and accelerating/braking, or the opposite a driver with slow steering wheel motions and gradual accelerating/braking.

The Moose test scenario is based on a real measurement which is used to determine the vehicle's properties – grip on the surface, driving dynamics, etc. (Constant (2012)). The main focus is on the vehicles behaviour and thus on its physical model in the Unreal Engine environment. However, user data can also be obtained, for example, when the vehicle is forced to operate without the use of an accelerator pedal therefore the only input is the steering wheel.

5. CONCLUSION

Creating a complex driver behaviour model proves to be a difficult task. Current cybernetics approach on this is derived from a 1960s model. Although it offers a simple approach that is quite easily measurable, it neglects a lot of the aspects that a car driver has. A different human control model was presented with a more sophisticated structure, that enables us to simulate real-life driver behaviour by updating an Internal Representation of a driver and studying the whole process of learning and adapting to certain situations. With that in mind, a car driving simulator was created with implemented scenarios that enable us to safely acquire information about the driver. The simulator is still a work-in-progress and there are multiple ways to extend it. There is a firm believe that in the future, this simulator could serve as a platform for driver behaviour analysis and automated driving simulations.

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